The Impact of St. Paul Vacant Buildings on Neighboring Property Values

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CLOSE TO HOME

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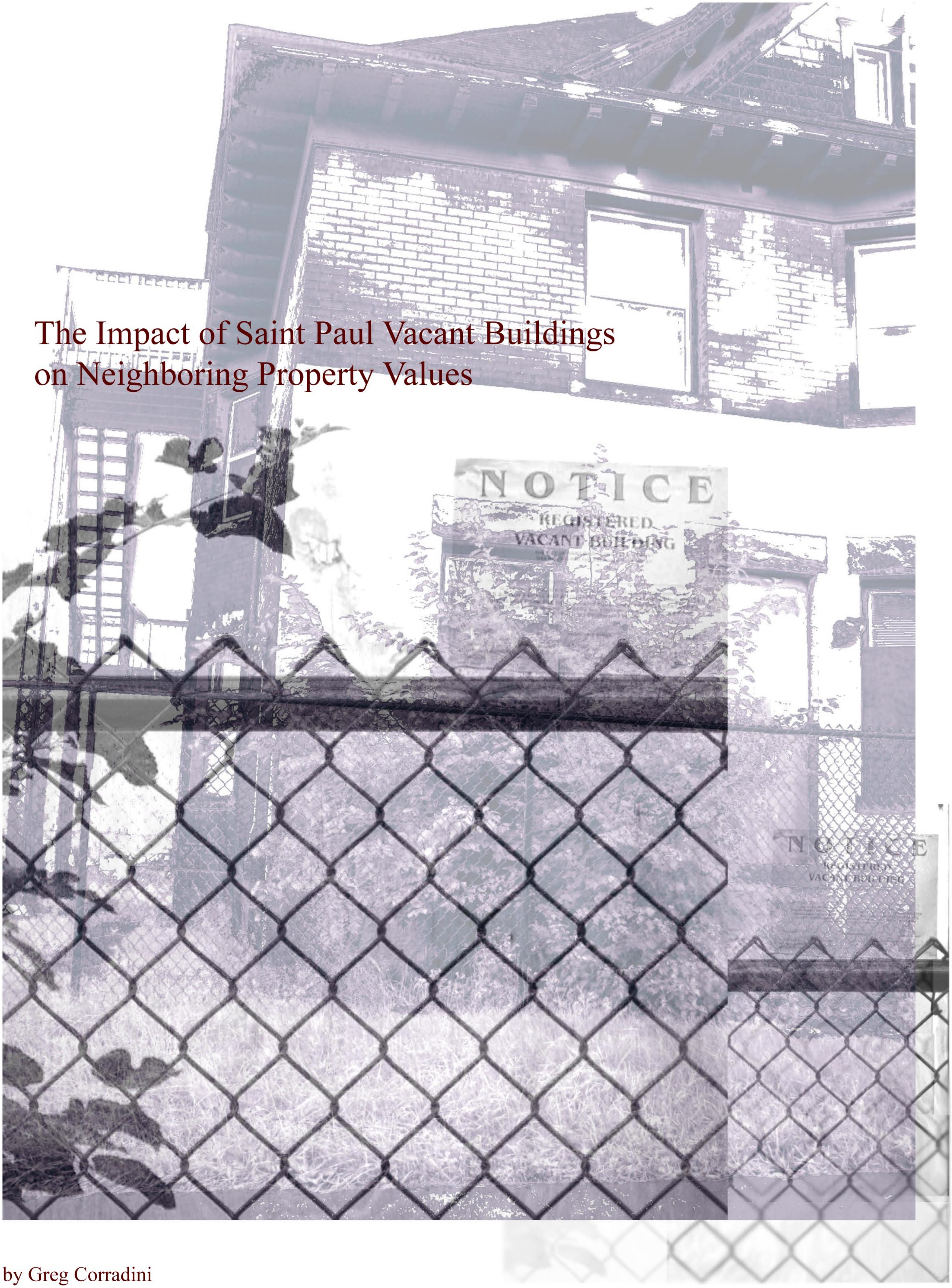


by Greg Corradini

Executive Summary

From 2001 to 2006, all District Councils in Saint Paul experienced an increase in vacant buildings (City Council Report). In neighborhoods with the largest increases, vacancies might be an indicator of neighborhood blight – a signal that a general pattern of economic disinvestment has taken its toll (Shlay and Whitman 16). If vacancies are truly a sign of distress, then they might also influence neighboring property values.

To investigate this assumption, we built a multivariate regression model to measure how vacant buildings impact Saint Paul single-family property values. The study used Saint Paul vacant building data from 2004 through 2006; neighborhood characteristics from Census 2000 data to control for variability between sale prices; and about 4,500 single-family sale transactions from 2005 to 2007.

Like other studies that estimate the impact of nearby foreclosures or vacancies on property value, our study shows that a vacant building's influence on property value increases with proximity. A vacant building has the largest impact within 450 ft of single-family properties; there, at least one vacant building decreases property value by an average 5.2365 percent. In this study, the median sale price is $200,000. We can interpret the –5.2365 percent estimate to mean that this median property might have sold for $211,052 – a difference of $11,052 – had a vacant property not been present. Does this mean that all Saint Paul single-family homes with at least one vacancy within 450 ft should expect a decrease in property value by 5.2365 percent? Not necessarily. This study only determines the average decrease in property value. But we can determine a range of property-value decrease within which we are quite confident all Saint Paul single-family homes are affected; we are 95 percent confident single-family homes in 2005 and 2006 experienced an average decrease in property value between 4 and 6.5 percent – an average loss of $8,247 to $13,895 for the median property.

A vacant property has less influence on single-family homes beyond 450 ft. We estimate at least one vacant building negatively impacts property values by an average 2.5478 percent if it falls between 450 ft and 600 ft of a single-family unit. For the median property value, this translates into an average loss of $5,161 with 95 percent confidence that the average loss is between $1,817 and $8,561.

From 600 ft to 750 ft, we estimate at least one vacant building decreases single-family property values by an average 1.9582 percent, an average loss of $3,995 for the median property value with 95 percent confidence that the average loss is between $481 and $7,570. Vacant buildings still continue to decrease single-family property values beyond 750 ft, but these estimates are not statistically significant.

For the 4,500 single-family homes in our study, this means the estimated average loss of property value totals more than $19 million with 95 percent confidence that the average net loss is between $12 million and $27 million. This is a conservative estimate. These estimates do not account for the impact vacancies had on apartments, multifamily residential, commercial and condominiums. Furthermore, this cumulative estimate does not gauge average property-value losses for single-family homes that *were not* on the market those years.

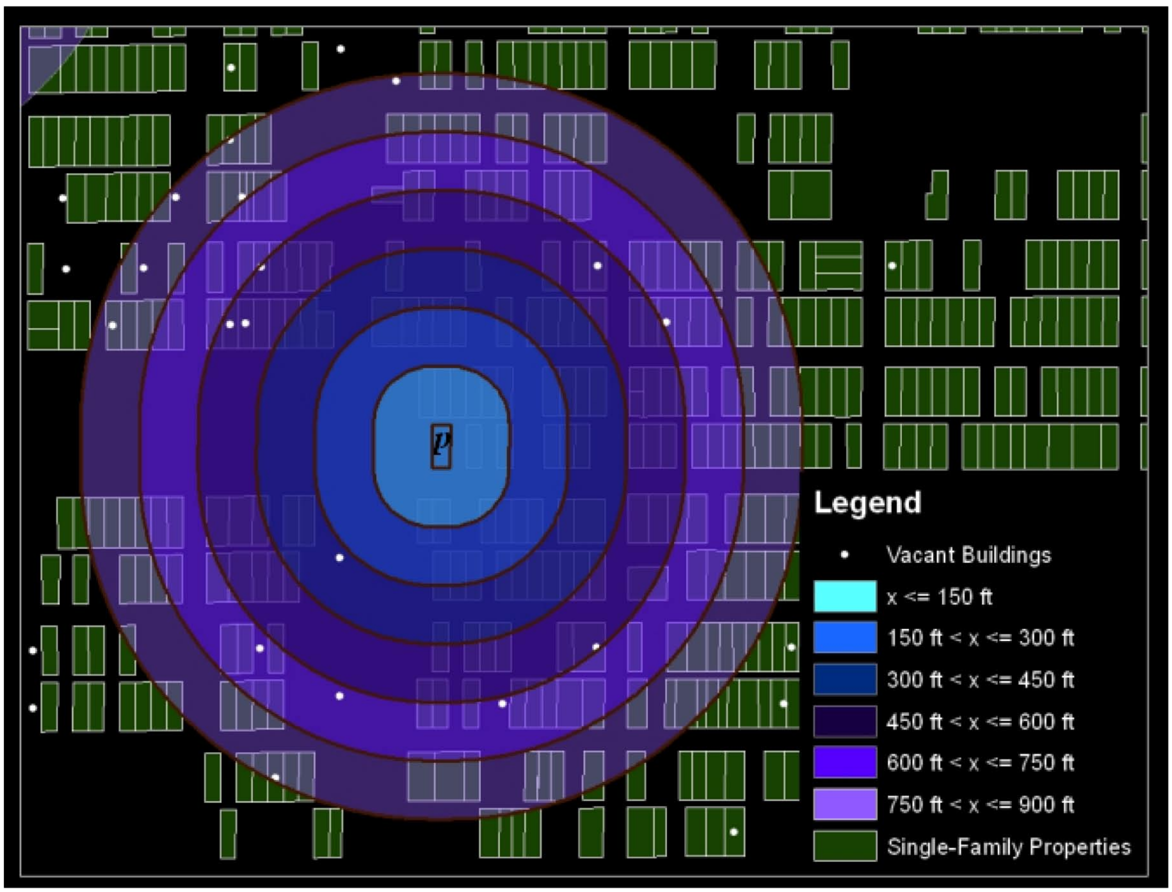
While this study determines the independent effect of the nearest vacancy on single-family property values, it is only the tip of the iceberg. More questions should be asked, more research conducted: What is the impact of the second nearest vacancy on property value? What is the cumulative impact of vacancies at different distances? How does the relationship – the interaction – between foreclosures and vacancies affect proximate property values?

Taken together these questions address neighborhood-specific issues – especially for those single-family homes in the middle of large vacant clusters. We might expect these property values to be disproportionately affected by vacancies than the average Saint Paul single-family home. For District Councils with high concentrations of vacancies such as Dayton's Bluff, Thomas-Dale and Payne-Phalen, these questions are imperative.

Methodology: The multivariate regression model

To estimate the independent effect of vacant buildings on single-family property values, we needed to build a multivariate regression model – also known as a pricing model. The independent effect allows us to estimate the portion of property-value variation explained by the nearest vacancy when all other measured factors are assumed equal. To help interpret how distance plays a role in this model, 150 ft buffers served as containers for the nearest vacancy. Figure 1 presents a visual representation of the vacant buffers in the model.

Figure 1. Illustration of Vacant Buffers



Our dependent variable in the equation below, *p*, is the natural log of sale value:

$$Ln(p) = \eta_0 + \eta_1 X + \eta_2 Z + \eta_3 OneBuff + \eta_4 TwoBuff + \eta_5 ThrBuff + \eta_6 FourBuff + \eta_7 FiveBuff + \eta_8 SixBuff + \eta_9 Vac$$

A vector of property characteristics is represented by X, which holds such variables as the natural log of lot area, number of stories, garage and external wall type, etc. Z represents the vector of neighborhood characteristics such as race per 2000 census block group. The six buffer variables represent the different distance intervals in Figure 1 from nearest to farthest. Vac is a variable that measures if our target parcel is vacant. Table 4 contains a full list of parcel attributes and definitions used as independent variables in the regression model.

A program queries vacancies and calculates the nearest distance to a vacant building for each single-family parcel in the study. The logic of the program – written with Python and the ArcGIS geoprocessing object – can be summarized in the following pseudo code:

1 For each parcel, select all vacant buildings within 33,000 ft (about half the diagonal distance of Saint Paul)
   - 1.1 If the target parcel was vacant within three months before its sale date, then flag it with a 1. Else flag it with 0
   - 1.2 Subselect only those buildings that stopped being vacant within three months before the target parcel's sale date AND are not our target parcel OR were open at the time of the sale AND are not our target parcel
      - 1.2.1 Calculate the distance to the nearest vacant building and update the continuous distance field
      - 1.2.2 Determine which 150 ft spatial buffer this distance falls within, and flag the appropriate buffer field with a 1. All other vacant buffer fields are flagged with 0

There are a few assumptions built into the above program. First, we chose a time interval before a home's sale date because we assumed a building that stopped being vacant might still affect nearby property values. However, the vacant literature contained nothing on what this window of time might be. One year and six-month time intervals seemed too generous, but a three-month window is an arbitrary date nonetheless. In the absence of these recommendations, MLS data could be used to provide time-interval estimates (Goetz). For example, the average number of days Saint Paul single-family homes stayed on the market might be used as a substitute. This study only tried using a three-month time interval.

Second, the spatial categories considered in this model only accounted for the first 900 ft from a single-family home. Since the first selection grabs all vacancies within 33,000 ft, more 150 ft buffers could be created beyond 900 ft. These would estimate how at least one vacancy at greater distances impacts property values. We actually ran different models with 150 buffers beyond a quarter of a mile – 1,320 ft. However, the coefficients at greater distances aren't significantly different than zero, and the final models in table 1 and table 2 only include buffers within 900 ft.

Third, distance intervals other than 150 ft buffers could have been used in the study. However, we began this project by looking for role models – different studies to use as roadmaps for our own. The study we stayed closest to measured the impact of abandonment on property values in a few different ways. In one model, Anne Shlay and Gordon Whitman used 150 buffers to gauge the physical proximity of abandonment (21).

It turns out the average single-family parcel depth in our study is about 130 ft. Therefore, each vacant buffer is a little longer than this average parcel depth.

Single-family property attributes and sale transactions were collected from a few sources. A Ramsey County parcel shapefile provided recent sale dates and values for most properties in Saint Paul. Other important property information needed for the regression model such as garage information, number of stories and bathrooms were absent or incomplete.

To get more information about each single-family home, we turned to IRIS, a web-based GIS developed by PropertyKey Inc. The Neighborhood Development Alliance (NeDA) has a membership to download data from IRIS. For different membership rates, PropertyKey offers access to different IRIS databases. According to PropertyKey support staff, the property database that NeDA subscribes to is a composite of county data and some MLS attributes. We used ODBC connections with Python to add fields, calculate new property IDs and format sale dates for the IRIS data. We then compared the shapefile records with the IRIS records. There were discrepancies between the sale dates and values. In these cases, we gave precedence to the county data.

We then bought a single-family dataset from Ramsey County Property Records and Revenue. This dataset contained the most recent, single-family true market sales between 01/01/2005 and 01/01/2007 as well as more property characteristics. Assessors distinguish between true market sales, which they call good sales, and bad sales, which include but are not limited to foreclosure sales, sheriff sales and sales between relatives.

Together these sources gave us 4,761 single-family properties. Once we removed all properties with any missing value, our sample contained 4,495 properties.

The Center for Urban and Regional Affairs (CURA) at the University of Minnesota provided the shapefile of vacant building data. This data contained information on vacancies from 1992 through the third quarter of 2006 that were collected by Saint Paul inspectors. There are a number of helpful fields in this shapefile that allowed us to pinpoint when vacancies ended and were still open. The "ENDDAY" column contained the dates when vacant buildings stopped being vacant. These end dates were coordinated with quarterly binary fields. If a building stopped being vacant on 12/01/2005, then the calendar quarter field "Q4_05" was flagged with a 1 to indicate the property was vacant during this quarter.

In our study, we only used vacant buildings that had end dates between 01/01/2004 and 10/26/2006, the last date that a vacant building was recorded in the data. The type of buildings included in our vacant sample are duplexes, mixed-use, commercial, multi-family residential and single-family residential. All buildings where the "OUTCOME" = 'Unknown' were removed.

We used two sets of neighborhood indicators in the regression model to control for the variability of sale prices between neighborhoods. A District Council binary variable was created for all parcels that fell within a particular district council. For example, if a handful of parcels are located within District Council 3, then a binary field indicating District Council 3 was updated with a 1.We used a spatial join in ArcGIS to determine in which district each parcel fell.

The second set of neighborhood characteristics contained racial category percentages for 2000 census block groups. We spatially joined parcels to block groups with ArcGIS. We then calculated percentages for each block group.

Note that other neighborhood characteristics could be used as controls. For example, one might expect crime to be highly correlated with sale values. We could determine how many single-family homes were located near different types of crimes and use the results as neighborhood variables. Foreclosure data, mortgage application data and utility records could also be used as variables. In short, the more neighborhood variables we use to control for variability in sale values limits the chance that a lurking variable might impact the model's results.

For this study, some neighborhood variables were excluded because we didn't have the time or connections to collect data. For other variables such as foreclosures, we aimed to include variables in the model that have high correlations with sale value, but do not interact greatly with vacancies. Foreclosures posed a problem because we assume they have a strong relationship with vacancies – a home can become vacant if it is foreclosed and cannot be sold.

Analysis results

The coefficient estimates for the multivariate model are shown in table 1. Looking at the variables of interest – our vacant buffer variables – we can see that a vacant property's influence on sale value decreases with distance. These results are expected and they support what was found in previous studies on the secondary impacts of vacancies.

In 1997, Goetz, Cooper, Theile and Lam used a hedonic pricing model to measure the effect that vacant outcomes – whether a vacancy was rehabilitated, razed or reoccupied – had on nearby property values. Citing other studies that gauge the effect of nearby phenomena on property values, the researchers decided vacant outcomes have "an impact for at least one-eighth of a mile in each direction" when they built their model. "Thereafter the effect diminishes until disappearing outside of three-quarters of a mile or one mile" (19).

Our results show similar trends. Within one-eighth of a mile or about 660 ft, the presence of at least one vacancy has the greatest influence on the natural log of property value for single-family homes.

Table 1. Estimates of Single-Family Property Value with Six Buffers

Variables	Estimate	Std. Error	t-value	p-value
Constant	8.67831	0.106574	81.430	0.0000
LGSFLA	0.422558	0.0128098	32.987	0.0000
LGLOTFT	0.128661	0.00815026	15.786	0.0000
DIST1	-0.307675	0.0127727	-24.088	0.0000
DIST2	-0.299758	0.0113555	-26.398	0.0000
DIST3	-0.215117	0.0190177	-11.311	0.0000
DIST4	-0.319938	0.0138492	-23.102	0.0000
DIST5	-0.314664	0.0122131	-25.765	0.0000
DIST6	-0.279749	0.0123380	-22.674	0.0000
DIST7	-0.293648	0.0185733	-15.810	0.0000
DIST8	-0.0304879	0.0218370	-1.396	0.1627

DIST9	-0.284816	0.0152374	-18.692	0.0000
DIST10	-0.128095	0.0127964	-10.010	0.0000
DIST11	-0.213576	0.0136608	-15.634	0.0000
DIST12	-0.0320117	0.0212311	-1.508	0.1317
DIST13	-0.0253548	0.0137760	-1.841	0.0658
DIST14	0.0104850	0.0110707	0.947	0.3436
DIST16	0.111955	0.0205978	5.435	0.0000
PERCASIAN	-0.00134177	0.000317924	-4.220	0.0000
PERCHISP	-0.00355100	0.000477789	-7.432	0.0000
PERCAFAM	-0.00344892	0.000336809	-10.240	0.0000
ONEBATH	-0.190274	0.0146818	-12.960	0.0000
TWOBATH	-0.146801	0.0139859	-10.496	0.0000
GARAGE	0.0558582	0.00693827	8.051	0.0000
ASBESTOS	-0.202309	0.0155802	-12.985	0.0000
ONESTORY	-0.0634193	0.00775077	-8.182	0.0000
RMTOT	0.0134381	0.00247694	5.425	0.0000
DECK	0.0328011	0.00629738	5.209	0.0000
SPRSALE	-0.0113482	0.00751496	-1.510	0.1311
WINSALE	-0.0433383	0.00728326	-5.950	0.0000
SUMSALE	0.00233550	0.00715924	0.326	0.7443
ALVINYL	-0.148457	0.0137685	-10.782	0.0000
STUCCO	-0.120891	0.0136890	-8.831	0.0000
FRAME	-0.121384	0.0139800	-8.683	0.0000
ONEBUFF	-0.0557332	0.0118595	-4.699	0.0000
TWOBUFF	-0.0513353	0.00887698	-5.783	0.0000
THRBUFF	-0.0549613	0.00809145	-6.793	0.0000
FOURBUFF	-0.0254581	0.00838603	-3.036	0.0024
FIVEBUFF	-0.0197513	0.00886466	-2.228	0.0259
SIXBUFF	-0.0130808	0.00920357	-1.421	0.1553
VAC	-0.0353313	0.0332623	-1.062	0.2882
R Squared		0.819323		
Sigma hat		0.157929		
N		4495		

Note: The dependent variable is the natural log of sale value

Notice that we're talking about the average decrease in the *natural log* of property value as it is represented above in table 1. The dependent variable in our model is the natural log of property value because it is normally distributed more than property value alone. To interpret table 1 and table 2 buffer estimates, we need to transform the coefficients using the following equation:

$$\text{Average percent decrease in property value} = (e^{\ln(x)} - 1)$$

where e is an irrational constant, and ln(x) is our natural log estimate. Once we perform these calculations, our estimates become:

$$\text{ONEBUFF} = e^{(-0.0557332)} - 1 = .9457914394 - 1 = -.0542085606$$
$$\text{TWOBUFF} = e^{(-0.0513353)} - 1 = .9499600955 - 1 = -.0500399045$$
$$\text{THRBUFF} = e^{(-0.0549613)} - 1 = .9465217776 - 1 = -.0534782224$$
$$\text{FOURBUFF} = e^{(-0.0254581)} - 1 = .9748632249 - 1 = -.0251367751$$
$$\text{FIVEBUFF} = e^{(-0.0197513)} - 1 = .980442479 - 1 = -.019557521$$
$$\text{SIXBUFF} = e^{(-0.0130808)} - 1 = .9870043818 - 1 = -.0129956182$$

Therefore, a vacant house within 150 ft decreases neighboring property values on average by –5.4208 percent with 95 percent confidence the average decrease is between 3.1961 and 7.5944. In the next two buffers – 150 ft to 300 ft and 300 ft to 450 ft – we still see an average decrease in property value near 5 percent.

As Goetz, Cooper, Theile and Lam assumed, the impact changes as we move toward one-eighth of a mile. If at least one vacancy occurs between 450 ft and 600 ft, we estimate the average decrease in property value to be 2.5136 percent with 95 percent confidence the average decrease is between 0.8976 and 4.1033 percent. Past one-eighth of a mile, a vacant building decreases property value by an average 1.9557 percent with 95 percent confidence the average decrease is between 0.2369 and 3.6440 percent. At a distance between 750 ft and 900 ft, a vacancy decreases property value an average 1.308 percent, but it is not statistically significant.

Look again at the first three buffers from table 1. Our estimates seem to confound the idea of a decreasing trend. Within 150 ft, the average decrease is 5.4 percent. From 150 ft to 300 ft, the average decrease is about 5 percent. And then from 300 ft to 400ft, the average decrease is greater than it was the buffer before – now 5.3 percent. We expect closer vacant buildings to have more influence than those at greater distances. Then how do we explain this ripple between buffers two and three?

The data in this instance might be misleading. Assume there is overlap between the effects of the first three buffers; that is, a vacancy at 280 ft has a similar impact on property value as a vacancy at 310 ft even though they are in different buffers. If this is true, then the anomaly we are witnessing only means that these buffers are not truly distinct – they aren't significantly different than each other.

To test this assumption, we used the model comparison in figure 2 where our null hypothesis was the model with the first three buffers grouped and our alternative hypothesis was the model with all six buffers.

Figure 2. Model Comparison

NH: Combined buffer, excluded one, two, three discrete buffers
AH: Full model with six buffers, excluded combined buffer

NH Summary Analysis of Variance Table for Combined Buffer

Source	df	SS	MS	F	p-value
Regression	38	503.761	13.2569	531.73	0.0000
Residual	4456	111.095	0.0249316		

AH Summary Analysis of Variance Table without Combined Buffer

Source	df	SS	MS	F	p-value
Regression	40	503.766	12.5941	504.94	0.0000
Residual	4454	111.09	0.0249417		

$$F = \frac{(RSS_{NH} - RSS_{AH}) / (df_{NH} - df_{AH})}{(RSS_{AH} / df_{AH})}$$

$$F = \frac{(111.095 - 111.090) / (4456 - 4454)}{(111.090 / 4454)}$$

F = .1002340445

F dist. with (2, 4454) df, value = 0.100234, upper-tail probability = 0.904628

Conclusion: Can't reject NH

As the conclusion highlights, we found that whatever differences may exists between the two models are two small for this study to determine. Therefore, our focus shifts from the model with six buffers in table 1 to the model with combined buffers and estimates in table 2 below. The executive summary at the beginning of this article contains the vacancy estimates from table 2 also.

Table 2. Estimates of Single-Family Property Value with Combined Buffer

Label	Estimate	Std. Error	t-value	p-value
Constant	8.67775	0.106508	81.475	0.0000
DIST1	-0.307684	0.0127701	-24.094	0.0000
DIST10	-0.128105	0.0127938	-10.013	0.0000
DIST11	-0.213646	0.0136527	-15.649	0.0000
DIST12	-0.0320006	0.0212266	-1.508	0.1317
DIST13	-0.0252978	0.0137726	-1.837	0.0663
DIST14	0.0105536	0.0110672	0.954	0.3403
DIST16	0.112009	0.0205933	5.439	0.0000
DIST2	-0.299794	0.0113513	-26.410	0.0000
DIST3	-0.215183	0.0190120	-11.318	0.0000
DIST4	-0.319896	0.0138441	-23.107	0.0000
DIST5	-0.314621	0.0122101	-25.767	0.0000
DIST6	-0.279753	0.0123351	-22.679	0.0000
DIST7	-0.293940	0.0185577	-15.839	0.0000
DIST8	-0.0303815	0.0218300	-1.392	0.1641
DIST9	-0.284715	0.0152326	-18.691	0.0000
FRAME	-0.121367	0.0139771	-8.683	0.0000
GARAGE	0.0559297	0.00692707	8.074	0.0000
LGLOT	0.128660	0.00813716	15.811	0.0000
LGSFLA	0.422613	0.0128060	33.001	0.0000
ONEBATH	-0.190236	0.0146785	-12.960	0.0000
ONESTORY	-0.0634269	0.00774918	-8.185	0.0000
PERCAFAM	-0.00344409	0.000336236	-10.243	0.0000
PERCASIAN	-0.00133940	0.000317659	-4.216	0.0000
PERCHISP	-0.00354336	0.000477306	-7.424	0.0000
DECK	0.0328836	0.00629194	5.226	0.0000
RMTOT	0.0134294	0.00247631	5.423	0.0000
TWOBATH	-0.146777	0.0139828	-10.497	0.0000
SPRSALE	-0.0113813	0.00751295	-1.515	0.1299
SUMSALE	0.00237943	0.00715706	0.332	0.7396
WINSALE	-0.0433465	0.00728159	-5.953	0.0000
STUCCO	-0.120862	0.0136845	-8.832	0.0000
ALVINYL	-0.148407	0.0137651	-10.781	0.0000
ASBESTOS	-0.202330	0.0155769	-12.989	0.0000
ONETWOTHR	-0.0537867	0.00682478	-7.881	0.0000

FOURBUFF	-0.0254787	0.00838229	-3.040	0.0024
FIVEBUFF	-0.0197768	0.00886229	-2.232	0.0257
SIXBUFF	-0.0130960	0.00920139	-1.423	0.1547
VAC	-0.0351932	0.0332461	-1.059	0.2899
R Squared		0.819315		
Sigma hat		0.157897		
N		4495		

Note: The dependent variable is the natural log of sale value

Before we interpret the estimates of the new model above, we need to transform them from natural log:

$$\text{ONETWOTHR} = e^{(-0.0537867)} - 1 = .9465217776 - 1 = -.0534782224$$
$$\text{FOURBUFF} = e^{(-0.0254787)} - 1 = .9748632249 - 1 = -.0251367751$$
$$\text{FIVEBUFF} = e^{(-0.0197768)} - 1 = .980442479 - 1 = -.019557521$$
$$\text{SIXBUFF} = e^{(-0.0130960)} - 1 = .9869893795 - 1 = -.01301063205$$

A vacant building has the largest impact within the first 450 ft of single-family properties; there, at least one vacant building decreases property value by an average 5.2365 percent. In this study, the median sale price is $200,000. We can interpret the –5.2365 percent estimate to mean this median property might have sold for $211,052 – a difference of $11,052 – had a vacant property not been present.

To figure out what the median property could sell for if a vacant building had not been present, we used the following calculation:

$$P = P^* / (1 - \beta_{buffer})$$

where P is the estimated property value had a vacant building not been present, P* is the actual sale value and β_{buffer} is my coefficient estimate for a buffer variable.

The first buffer coefficient – onetwothr – is not saying that all Saint Paul single-family homes with at least one vacancy within 450 ft should expect a decrease in property value of 5.2365 percent. This study only determines the average decrease in property value. But a 95 percent confidence interval will help frame how vacancies affect all Saint Paul single-family homes; we are 95 percent confident single-family homes in 2005 and 2006 experienced an average decrease in property value between 4 and 6.5 percent – an average loss of $8,247 to $13,895 for the median property.

A vacant property has less influence on single-family homes beyond 450 ft. We estimate at least one vacant building negatively impacts property values by an average 2.5478 percent if it falls between 450 ft and 600 ft of a single-family unit. We are 95 percent confident the average decrease is between .9004 and 4.1046 percent. For the median property value, this translates into an average loss of $5,161 with 95 percent confidence that the average loss will be between $1,817 and $8,561.

From 600 ft to 750 ft, we estimate at least one vacant building decreases single-family property values by an average 1.9582 percent with 95 percent confidence the average decrease is between .2399 and 3.6369 percent. That is an average loss of $3,995 for the median property value with 95 percent confidence that the average loss is between $481 and $7,570. Vacant buildings still continue to decrease single-family property values beyond 750 ft, but these estimates are not statistically significant.

Total Property Value Loss

We used the equation $P = P^* / (1 - \beta_{buffer})$ to determine what each single-family property in our study could sell for had a vacancy not been present. We then took these new property-value estimates and subtracted the actual sale prices, which gave us their difference. Summing the differences gives us the total loss in property value.

For the 4,495 single-family homes in our study, this means the estimated average loss of property value totals more than $19 million with 95 percent confidence that the average net loss is between $12 million and $27 million. This is a conservative estimate. These estimates do not account for the impact vacancies had on apartments, multifamily residential, commercial and condominiums. Furthermore, this cumulative estimate does not gauge average property-value losses for single-family homes that *were not* on the market those years.

Table 4. Independent Variables and Descriptions

Variables	Descriptions
Neighborhood Variables	
DIST1	District Council = 1
DIST2	District Council = 2
DIST3	District Council = 3
DIST4	District Council = 4
DIST5	District Council = 5
DIST6	District Council = 6
DIST7	District Council = 7
DIST8	District Council = 8
DIST9	District Council = 9
DIST10	District Council = 10
DIST11	District Council = 11
DIST12	District Council = 12
DIST13	District Council = 13
DIST14	District Council = 14
DIST16	District Council = 16
Excluded Variable = District Council 15*	
PERCASIAN	Percent Asian per 2000 Block Group
PERCHISP	Percent Hispanic/Latino per 2000 Block Group
PERCAFAM	Percent African American per 2000 Block Group
Excluded Variable = Percent Anglo and Other	
Property Variables	
ONEBATH	Property has bathrooms >= 1 AND bathrooms < 2
TWOBATH	Property has bathrooms >= 2 AND bathrooms < 3
Excluded Variable = Property has bathrooms >= 3	
GARAGE	Property has garage
ASBESTOS	External Wall Type = Asbestos
STUCCO	External Wall Type = Stucco
FRAME	External Wall Type = Frame
ALVINYL	External Wall Type = Aluminum/Vinyl
Excluded Variable = External Wall Type = (Block,Brick,Stone)	
SPRSALE	Season of Sale = Spring
WINSALE	Season of Sale = Winter
SUMSALE	Season of Sale = Summer
Excluded Variable = Season of Sale = Fall	

ONESTORY	Property has stories >= 1 AND stories < 2
Excluded Variable = Property has stories >= 2	
RMTOT	Total number of rooms
DECK	Property has deck
LGSFLA	Natural Log of Finished Square Feet
LGLOTFT	Natural Log of Lot Area

Variables of Interest: Vacant Buildings

ONEBUFF	Vacant bldg <= 150 ft
TWOBUFF	Vacant bldg > 150 ft AND Vacant bldg <= 300 ft
THRBUFF	Vacant bldg > 300 ft AND Vacant bldg <= 450 ft
FORBUFF	Vacant bldg > 450 ft AND Vacant bldg <= 600 ft
FIVBUFF	Vacant bldg > 600 ft AND Vacant bldg <= 750 ft
SIXBUFF	Vacant bldg > 750 ft AND <= 900 ft
VAC	Target parcel was vacant within 3 months before sale date

***Note:** District Council 17 had only one single-family home, which was removed from study

References

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